A ROTATION TEST FOR BEHAVIOURAL POINT PROCESS DATA

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A common problem in animal behavior is determining whether the rate at which a certain behavioural event occurs is affected by an environmental or other factor. In the example considered later in this paper, the event is a vocalization by an individual sperm whale and the factor is the operation or non-operation of an underwater sound source. A typical experiment to test for such effects involves observing animals during control and treatment periods and recording the times of the events that occur in each. In statistical terminology, the data arising from such an experiment – the times at which events of a specified type occur – represent a point process (Cox & Lewis 1978). Events in a point process are treated as having no duration. Although this is not strictly correct for behavioural events, the approximation is reasonable when the duration of events is small in relation to the interval between them.

In some cases, under the null hypothesis of no treatment effect, behavioural events can be assumed to follow a stationary Poisson process. Under this model, the intervals between successive events are independent and, conditional on their number, the events are uniformly distributed over the observation period. As described below, when the Poisson assumption is valid, a statistical test to determine whether event rate changes under treatment can be based on the binomial distribution. In many cases, however, the Poisson model has been shown to be invalid for behavioural events. This is the case, for example, when events occur in bouts (Slater & Lester 1982; Sibly et al. 1990; Haccou & Meelis 1992). As illustrated below, when behavioural events do not follow a Poisson process, the binomial test can give misleading results. A number of methods are available to test whether a point process is Poisson based on the uniformity result mentioned above (Stephens 1986). If a point process cannot be assumed to be Poisson,

one option is to use a test that is valid under a particular alternative to the Poisson model. Unfortunately, while it is often easy to show that a point process is not Poisson, it can be difficult to specify an appropriate alternative model. The purpose of this paper is to describe and illustrate the use of a simple nonparametric method that can be used to analyze behavioural point process data even if the process generating the data is unknown.

A Rotation Test

Suppose that events are observed over the period (0, *T*), and that the total times under control and treatment conditions are T_C and T_T, respectively (with $T = T_C + T_T$). Assume that, under control conditions, events follow a stationary Poisson process with rate λ_C and that, under treatment conditions, events follow an independent Poisson process with rate λ_T. Under this model, interest centers on testing the null hypothesis $H_o : \lambda_C = \lambda_T$ of no treatment effect. Let the random variables N_C and N_T be the numbers of events occurring under control and treatment conditions, respectively, and let $N = N_C + N_T$ be the total number of events. Conditional on the observed value *n* of *N*, under H_o, N_C has a binomial distribution with *n* trials and success probability T_C / T. The null hypothesis can be rejected at significance level α if the observed value of N_C is below the lower $(\alpha / 2)$ quantile or above the upper $(\alpha / 2)$ quantile of this binomial distribution. Provided *n* is not too small and T_C / T is not too close to 0 or 1, the binomial distribution

can be approximated by a normal distribution with mean nT_C / T and variance $nT_C T_T / T^2$, so that H_o can be rejected at approximate significance level α if:

$$\left| \frac{TN_C - nT_C}{\sqrt{nT_C T_T}} \right| > \Phi^{-1}(\alpha/2) \qquad (1)$$

where $\Phi^{-1}(\alpha/2)$ is the upper $(\alpha/2)$ quantile of the standard normal distribution.

Behavioral events often exhibit clustering in time beyond what is expected under a Poisson process. As illustrated below, the binomial test may fail in such cases because the underlying randomization scheme – distributing *n* events at random over the observation period – fails to capture internal structure in the events that is present even under the null hypothesis. A randomization procedure that does preserve this internal structure can be visualized in the following way. Transform the observation period into a circle by joining its end to its beginning. This is sometimes referred to as imposing a periodic boundary condition. Keeping the partition of the observation period into control and treatment segments fixed, displace the events by the same random rotation. Let t_j be the time of the *j*th event. Its time under this rotation scheme is given by:

$$t_j^* = \begin{cases} t_j + U & t_j + U < T \\ t_j + U - T & t_j + U > T \end{cases} \qquad (2)$$

where U is a uniform random variate over the interval (0, T). By displacing each event by the same random angle, this procedure preserves the internal structure of the events except at the beginning of the original observation period, where events originally near T are now in proximity to events originally near 0. Provided n is not too small, the effect of this concatenation is negligible. The test proceeds by approximating the distribution of N_C under the null hypothesis from values produced by a large number of random rotations. The null hypothesis is then rejected at significance level α if the observed value of N_C lies below the lower or above the upper $\alpha/2$ quantile of this distribution. This general approach was originally proposed by Harkness & Isham (1983) for testing association between two two-dimensional point processes observed on a rectangle. The test has been applied by Miller et al (2004a, b), but a detailed description of the test including assessment of its validity and power has not previously been published.

To summarize, the steps involved in the rotation test are:

1. Express the data as a set of behavioral event times over the observation period (0, T).
2. Calculate the number N_c of events occurring during the control period.
3. Generate a rotated set of behavioural event times according to (6).
4. Calculate the number N_{c_rot}, of events in the rotated set falling in the original control time period.

5. Repeat steps 3-5 many times to obtain a distribution for N_{c_rot} and assess significance by comparing the the observed value of N_C to the quantiles of this distribution.

Test Performance

In this section, we assess the performance of the binomial and rotation tests under three point process models: the stationary Poisson process, the one-dimensional Thomas process (Thomas 1949), and an exponential autoregressive (EAR) model (Lawrance & Lewis 1979). The Thomas process is a classical model of clustering in point process data, while the EAR model gives rise to clustering through positive autocorrelation in the intervals between events. No claim is made that either of these models is necessarily appropriate for a particular behavioural point process. Instead, they are used here as plausible alternatives to the Poisson process.

In a Thomas process, initiating events follow a stationary Poisson process with rate μ. Each initiating event gives rise to an additional number of offspring events. The numbers of these offspring are independent Poisson random variables with mean θ. Let s_o be the time of an initiating event and suppose that it gives rise to k offspring. The times of these offspring are given by $s_j = s_o + \delta_j$, $j = 1, 2, \ldots, k$, where $\delta_1, \delta_2, ..., \delta_k$ are independent random intervals with common distribution function F. The process consists of the union of the initiating events and their offspring. The Thomas process is stationary with overall rate $\mu(1+\theta)$. However, it is over-dispersed in relation to the Poisson

process with the same rate. For example, for the Thomas process, the variance of the number of events occurring in a unit interval is $\mu(1+3\theta+\theta^2)$ instead of $\mu(1+\theta)$ for the Poisson process with the same overall rate.

In contrast to the Thomas process, which is a model of the event times, the EAR process is a model for the intervals between events. Let $d_j = t_j - t_{j-1}$ be the interval between events $j-1$ and j. Under the Poisson model, the intervals $d_1, d_2, ...$ are independent exponential random variables. In contrast, under the EAR model, the sequence of intervals follows the autoregressive process:

$$d_j = \rho d_{j-1} + \varepsilon_j \qquad (3)$$

where ε_j is equal to 0 with probability ρ and equal to an exponential random variable with mean $1/\lambda$ with probability $1-\rho$. The EAR process is stationary with overall rate λ and autocorrelation function $Corr(d_j, d_{j-h}) = \rho^h$. The positive dependence between successive intervals gives rise to clustering of events.

Although it is possible to make some progress analytically, for the purpose of this paper we present some results from a small simulation study. The goal of the first part of this study was to assess the validity of the nominal significance levels of the binomial and rotation tests under the three point process models outlined above. This involved repeatedly simulating point process data from these models under the null hypothesis and

applying both tests at the nominal 0.05 significance level. For a valid test, the null hypothesis should be rejected at a rate equal to the nominal significance level. In the study described here, the observation period was taken to be the unit interval, with the first half corresponding to the control period and the second half to the treatment period. Results are presented in Table 1 for overall mean rates of 500 and 1000. For the Thomas process, the parameter θ was fixed at 1 while for the EAR process the parameter ρ was fixed at 0.5. Each entry in Table 1 was based on 1000 simulated data sets and each rotation test was based on 1000 random rotations. In the case of the Thomas process, we assumed that offspring events fell into the same sub-period as their initiating event. In practical terms, this amounts to the assumption that the displacements between offspring and initiating events are negligible in relation to the length of the periods of control and treatment conditions.

Turning to Table 1, it is clear that the binomial test is invalid for point process data generated by the Thomas and EAR processes. For these models, the estimated true rate at which the null hypothesis is falsely rejected is well above the nominal significance level. In contrast, the estimated true significance level for the rotation test is not significantly different from the nominal level for all three point process models.

The goal of the second part of the simulation study was to assess the power of the rotation test. Power is defined as the probability of rejecting the null hypothesis when the alternative hypothesis is correct. This probability will depend on the nature and magnitude of the departure from the null hypothesis, as well as on the amount of data.

As a rough guide, a test has good power if this probability is at least 0.8. The power study was based on the same general simulation procedure outlined above except that, for each of the point process models, the overall rate under treatment conditions was increased by a multiplicative factor *f* over its value under control. For the Thomas process, this was accomplished by increasing the rate μ of initiating events. As before, let λ_C and λ_T be the rates under control and treatment conditions, respectively. For the case here where the observation period is evenly divided between control and treatment, the overall rate λ is simply the average of λ_C and λ_T. Throughout this power study, this overall rate was held fixed by taking $\lambda_C = 2\lambda/(1+f)$ and $\lambda_T = f\,\lambda_C$.

The results of the power study are shown in Table 2. Results are presented for overall rates 500 and 1000 with the parameter θ of the Thomas process fixed at 1, the parameter ρ of the EAR process fixed at 0.5, and *f* = 1.5, 2, and 3. . As before, each entry in this table was based on 1000 simulated data sets and for each data set the rotation test was based on 1000 random rotations. For the Poisson case, results are presented for both the binomial test and the rotation test. In this case, the rotation test is less powerful than the binomial test, although it achieves good power in most of the cases considered here. As the binomial test is not valid for the Thomas and EAR processes, for these processes results are presented only for the rotation test. The power of the rotation test is quite similar for the two cluster processes. In general, the rotation test achieves good power provided the magnitude of the treatment effect and the overall rate of events are not too small.

In addition to the results presented in Table 2, we determined by simulation the minimum detectable effect size $f_{\min}$ – defined as the value of *f* for which the test at 0.05 significance level achieves a power of 0.8 – for the cases considered in Table 2. Results are presented in Table 3. In overall terms, the rotation test has good power once *f* reaches approximately 2.

An Application to Sperm Whale Response to Airgun Sounds

In this section, we apply the rotation test to some experimental data involving the exposure of a sperm whale to air-gun sounds. Air-guns are a source of loud, impulsive low-frequency underwater sound. They are generally deployed in towed arrays for geophysical exploration (Richardson et al. 1995). Air-gun arrays have very high source levels (Richardson et al. 1995; Caldwell & Dragoset 2000) and there is a concern that exposing sperm whales and other marine mammals to air-gun noise may have adverse impacts on their behavior (Gordon et al. 2003).

Because sperm whales use echolation to locate prey, one hypothesized behavioral impact of air-gun sound is a reduction in whale foraging rate. Sperm whales produce regular echolocation clicks almost continuously while foraging, interrupted only by short pauses and buzzes (short series of rapid echolocation clicks indicative of attempted prey capture (Whitehead 2003, Miller et al. 2004a)). Whales begin producing echolocation clicks during the descent phase of deep dives, stop clicking during or just prior to ascent,

239 and do not generally produce series of regular echolocation clicks while at the surface or
240 during shallow dives (Watwood et al. 2006). We therefore defined foraging periods as
241 the portions of deep dives between the start and end of regular echolocation clicks. The
242 behavioral event of interest was the production of echolocation buzzes, which serve as a
243 proxy for foraging rate.
244
245 The data used here were collected during controlled exposure experiments
246 conducted on the 2002 and 2003 Sperm Whale Seismic Study cruises. During the
247 experiments, dtags (Johnson & Tyack 2003) were attached to individual whales to record
248 sound and movement data during control conditions (no air-gun sound exposure) and
249 treatment conditions (air-gun sound exposure). Air-guns were fired every 15 seconds
250 during the treatment period. Detailed information on these experiments can be found in
251 Jochens & Biggs (2003, 2004) and Madsen et al. (2006). Here, we present data from a
252 single individual.
253
254 The behavioural record is shown in Figure 1. For this whale, the total time spent
255 foraging during the observation period was T = 5.89 hours, of which $T_C = 4.74$ hours was
256 under control conditions (the air-gun array was not operating) and $T_T = 1.15$ hours was
257 under treatment conditions (the air-gun array was in operation). A total of n = 153
258 echolocation buzzes were recorded, of which $N_C = 139$ occurred during control
259 conditions and $N_T = 14$ occurred during treatment conditions. The empirical rate of
260 events during control conditions was 29.3 events h^{-1} and the corresponding rate during

261 treatment conditions was only 12.2 events h^{-1}. The value of the binomial test statistic in
262 (1) is 3.43, which is significant at approximately the 0.0006 level.
263
264 For reasons connected to the spatial distribution of prey and whale foraging
265 behavior, we expected that the Poisson model underlying the binomial test was unlikely
266 to apply to this time-series of sperm whale foraging events. This expectation was
267 confirmed by an analysis of the intervals between events, which revealed positive
268 autocorrelation at short lags. As the intervals in a Poisson process are independent, this
269 autocorrelation is evidence of non-Poisson behaviour in the point process. We therefore
270 applied the rotation test to these data. The histogram of values of N_C based on 10,000
271 rotations is shown in Figure 2. Of these, 647 exceeded the observed value of 139 for an
272 estimated two-sided significance level of approximately 0.13. In contrast to the binomial
273 test, by conventional standards, the null hypothesis cannot be rejected by the rotation test.
274 It is not possible to calculate a priori power estimates for the sperm whale data set, since
275 we do not know the true process generating the buzz time series data, and thus we can not
276 produce the simulated data needed for power estimation.
277
278 **Discussion**
279
280 The rotation test is a general nonparametric approach that can be used when data exhibit
281 serial dependence. The purpose of this paper has been to describe, evaluate, and illustrate
282 this test in the specific context of testing for a treatment effect on the rate of a
283 behavioural point process. We have shown that, in this context, the rotation test works

well, maintaining the nominal significance level while providing high power when the data do not follow a Poisson process. In contrast, the binomial test is invalid in this case.

A common approach to analyzing behavioural point processes is to reduce the data to empirical rates within time bins (e.g, Cherry 1989; Mooring 1995; Paredes et al. 2005; Fernández-Juricic & Tran 2007). As a general proposition, binning point process data entails a loss of power (Dean & Balshaw 1997) and is not recommended. Moreover, the analysis of binned data is also affected by non-Poisson behaviour in the underlying point process. Briefly, if the underlying point process is Poisson, then the counts within bins will have Poisson distributions. Statistical methods for analyzing Poisson count data are reviewed in McCullagh & Nelder (1989). However, if the underlying point process is not Poisson, then the distribution of bin counts is also not Poisson and the results of these methods can be misleading (Paul & Banerjee 1998). A common alternative to the Poisson distribution for count data is the negative binomial distribution. Parametric methods for analyzing negative binomial data are available (e.g., Barnwal & Paul 1988; Paul & Banerjee 1998). The rotation test provides a nonparametric alternative.

Turning to the results of the previous section, it is clear that no general conclusion about the effect of air-gun noise on sperm whales can be drawn from the results of the single test presented here. However, it is also worth pointing out that the hypothesized effect of air-gun nose is a *reduction* in foraging. Had a one-sided test for such a reduction been performed, the significance level would have been around 0.065 which, in light of power considerations, is certainly suggestive of an effect.

Finally, although this paper has focused on the rotation test in the context of analyzing behavioural point process data, the same general method could be used in other situations. For example, Shapiro (2008) used a rotation test to determine whether the frequencies of different types of vocalizations in killer whales differed between behavioural states. In this case, the approach was used to account for serial dependence in vocalization type.

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Tables

Table 1. Validity of the binomial and rotation tests

	overall mean rate	
	500	1000
Poisson		
binomial	0.05	0.05
rotation	0.042	0.054
Thomas		
binomial	0.221	0.233
rotation	0.045	0.049
EAR		
binomial	0.247	0.251
rotation	0.052	0.052

The rate at which the null hypothesis of no treatment effect was falsely rejected in testing at the 0.05 significance level using the binomial test and the rotation test for data simulated from the Poisson, Thomas, and EAR models with overall mean rates of 500 and 1000. For the Thomas model, $\theta = 1$ and for the EAR model $\rho = 0.5$. Results are

based on 1000 simulations except for the binomial test under the Poisson model where the theoretical result is given.

Table 2. Power of the rotation test

	overall mean rate					
	500			1000		
	f			f		
	1.5	2	3	1.5	2	3
Poisson						
binomial	1	1	1	1	1	1
rotation	0.61	0.90	0.99	0.82	0.98	1
Thomas						
rotation	0.34	0.63	0.88	0.56	0.86	0.97
EAR						
rotation	0.37	0.64	0.86	0.54	0.83	0.98

The power of the rotation test at the 0.05 significance level is presented, for data simulated under the Poisson, Thomas, and EAR models when the mean rate under treatment is a factor *f* greater than that under control and when the overall mean rate is fixed at 500 and 1000. For the Thomas model, we always used $\theta = 1$; for the EAR model we always used $\rho = 0.5$. For the Poisson model, results are also given for the binomial test. Results are based on 1000 simulations.

Table 3. Minimum detectable effect levels.

	overall mean rate	
	500	1000
Poisson		
binomial	1.3	1.2
rotation	1.7	1.5
Thomas		
rotation	2.5	1.8
EAR		
rotation	2.7	2.0

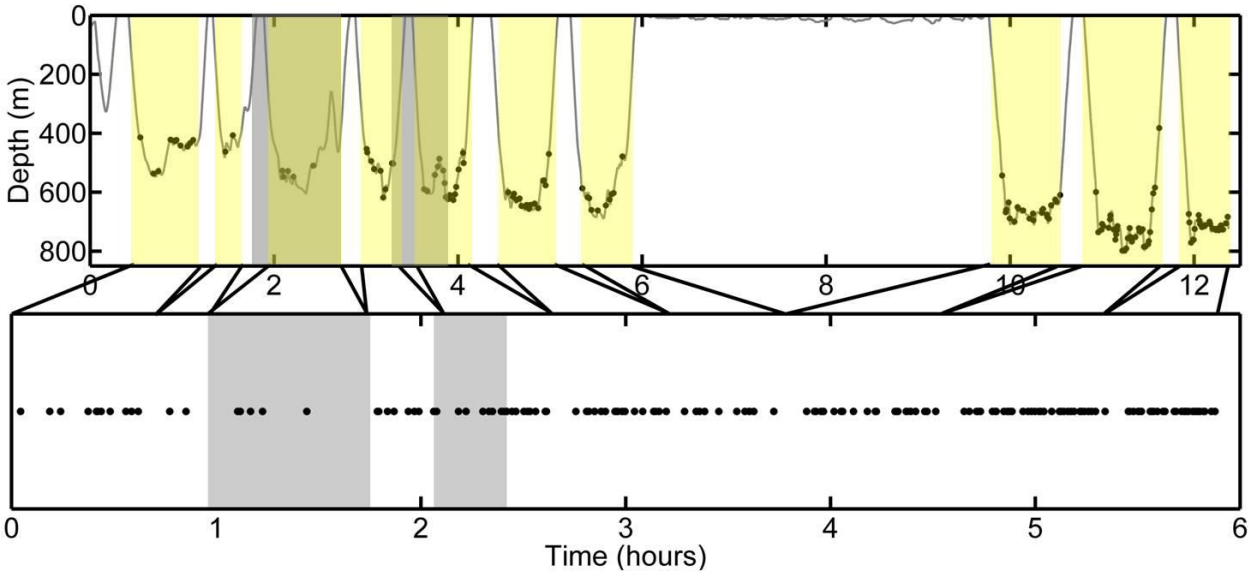
The minimum detectable effect size $f_{\min}$ – defined as the value of f for which the test at 0.05 significance level achieves a power of 0.8 – for the cases considered in Table 2. Results are based on 1000 simulations.

Figure Legends

Figure 1. Top panel: Dive profile of the tagged sperm whale. The grey line indicates whale depth, and black circles indicate the times of echolocation buzzes. Airgun exposure periods are shaded gray. Black lines connecting the top and bottom panels illustrate how dive ascents, descents and surface periods were cut from the dataset to produce the buzz time-series we analyzed. Only foraging periods (indicated by yellow shading) were included in the buzz time-series. Bottom Panel: Time-series of echolocation buzzes produced by the sperm whale during foraging periods. Black dots indicate the times of buzzes, and gray shaded areas indicate airgun exposure periods.

Figure 2. Histogram of values for N_C, the number of creaks during the control period, obtained in 10,000 rotations of the sperm whale dataset. (The value of N_C was 139 for the original, non-rotated dataset.)

478 **Figures**



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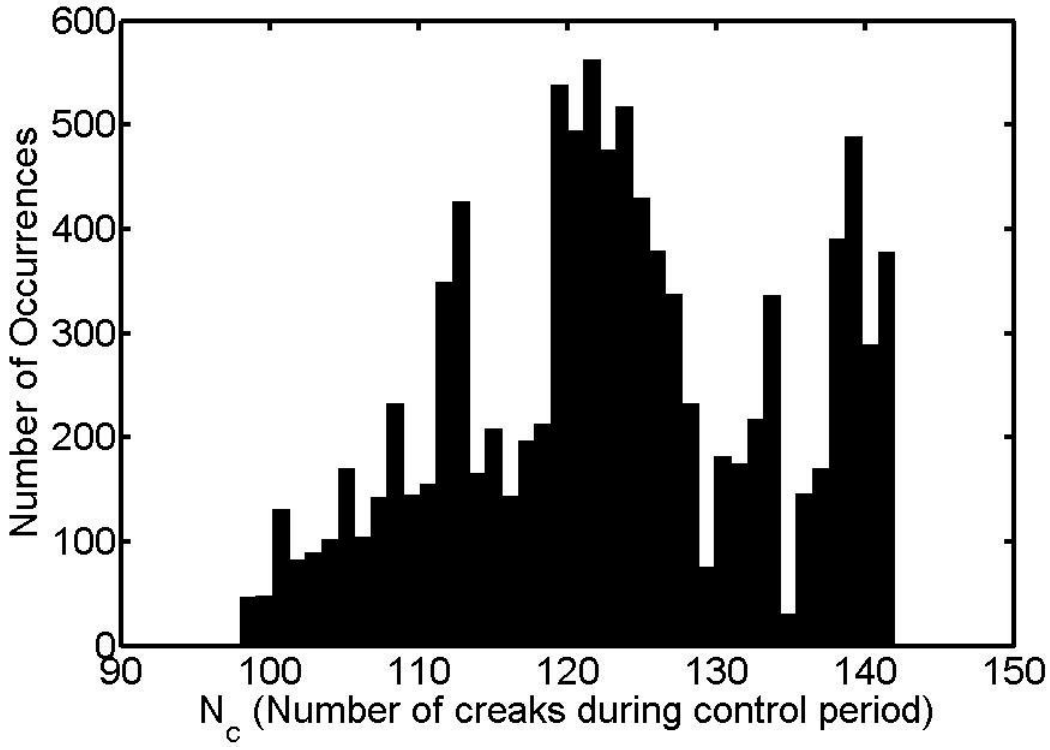

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